ATR ALGORITHM PERFORMANCE FOR THE BRTRC WICHMANN GROUND PENETRATING RADAR SYSTEM

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ABSTRACT

Many fielded sensors for UXO detection, such as electromagnetic induction (EMI) systems, are capable of attaining high detection rates. However, high probability of detection is often achieved at the expense of excessively high false alarm rates. To reduce the false alarm rate, other sensor modalities, such as ground penetrating radar (GPR), have been proposed. Ground penetrating radar is sensitive to discontinuities in the interrogated medium, rather than the presence of metal, and thus exploits a different phenomenology. With GPR, non-metallic objects, such as wood, plastic, and stone, as well as metallic objects, can be "seen" by the radar, potentially improving the detection of low metal content targets. The BRTRC Wichmann antenna is a GPR system that provides a high frequency radar signal with very low noise levels following the ground reflection. It has been demonstrated that an operator can learn to interpret the BRTRC Wichmann radar signal to detect and identify buried targets. The goal of the work presented here was to develop signal processing algorithms to automatically process the radar signals and differentiate between targets and clutter. Data was gathered at the Hand Held Metallic Mine Detector Performance Baselining test site developed by the Joint UXO Coordination Office. The BRTRC Wichmann antenna array was instrumented for digital capture of the received signal data, which was then processed separately. Several algorithms of increasing complexity have been applied to this data, and the results are presented. Preliminary results with a limited data set indicate that mines can be successfully differentiated from clutter.

1. INTRODUCTION

Many fielded sensors for UXO detection are capable of attaining high detection rates. However, high probability of detection is often achieved at the expense of excessively high false alarm rates. This is particularly true of electromagnetic induction (EMI) sensors, which are sensitive to the presence of metal, and thus respond to every piece of metallic debris on a site. Previously, it has been shown that the application of signal detection theory to EMI data results in substantially lower false alarm rates for UXO detection applications [1,2]. To further reduce the false alarm rate, other sensor modalities, such as ground penetrating radar, have been proposed. Ground penetrating radar (GPR) is sensitive to discontinuities in the electrical properties of the interrogated medium, rather than the presence of metal, and thus exploits a different phenomenology. Therefore, unique signals, which are dependent on the object composition, can be obtained from buried objects. Consequently, non-metallic objects, such as wood, plastic, and stone, as well as metallic objects, can be "seen" by the radar, potentially improving the detection of low metal content targets.

The BRTRC Wichmann antenna array, developed by Gunther Wichmann, provides a high frequency radar signal with very low noise levels following the ground reflection. Consequently, the signal from a buried object is not masked by the inherent noise in the system. It has been demonstrated that an operator can learn to interpret the BRTRC Wichmann GPR signal to detect and identify buried targets. The goal of this work was to develop signal processing algorithms to automatically process the radar signals produced by the BRTRC Wichmann ground penetrating radar system to differentiate between targets and clutter.

2. BRTRC WICHMANN GPR DATA

The Joint UXO Coordination Office at Ft. Belvoir, VA is sponsoring a series of experiments designed to establish a performance baseline for a variety of sensors [3,4]. This baseline will be used to measure the potential improvements in performance offered by advanced signal processing algorithms. In conjunction with this effort, data from low-metal content mines has been gathered using a variety of sensors. We have implemented a series of algorithms in order to evaluate performance for the BRTRC Wichmann antenna array.

The BRTRC Wichmann antenna array GPR data was gathered at the Hand Held Metallic Mine Detector Performance Baselining test site developed by the Joint UXO Coordination Office. This work was performed under the sponsorship of Roger Rogowski and Fred Clodfelter of BRTRC who provided programmatic and technical support for the data acquisition. The antenna array was instrumented for digital capture of the received signal data, which was then processed separately. Details concerning the data collection may be found in [4], and details of the JUXOCO test set are available in [3].

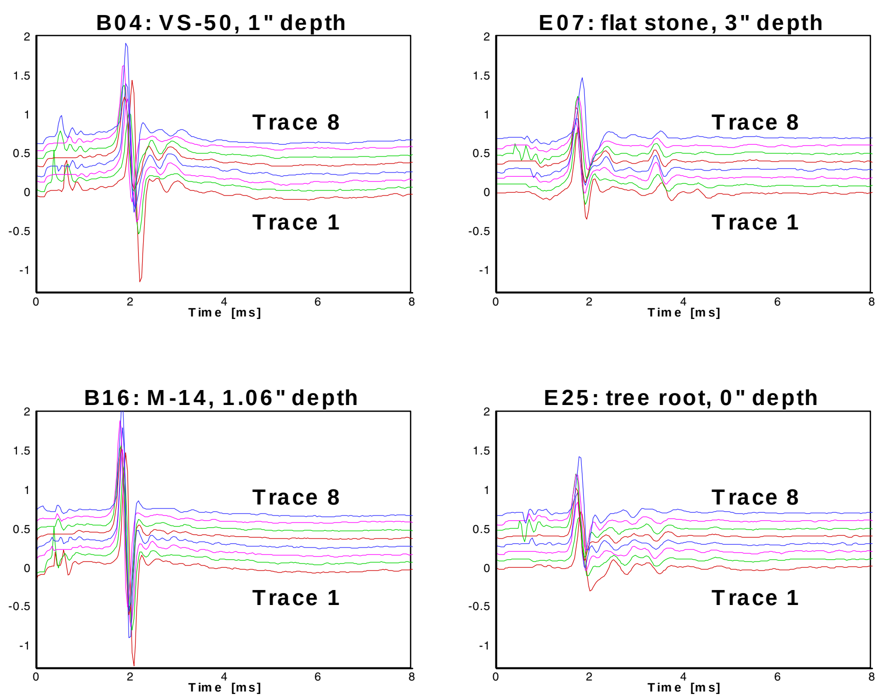

Figure 1: Example BRTRC Wichmann antenna array GPR signals for mine (grid locations B04 and B16) and clutter (grid locations E07 and E25) targets.

The data collected over each target consists of 8 cross-track traces at 5 down-track scans. The down-track scans were recorded at distances of -4, -2, 0, 2, and 4 inches relative to the center of the target for small targets. These distances were increased to -8, -4, 0, 4, and 8 inches for large targets. The distance between each of the cross-track traces is approximately 1.5 to 2 inches. Examples of the BRTRC Wichmann antenna array GPR signals for mine and clutter targets are shown in Figure 1. Each of these examples is taken from the scan centered over the target, and the traces have been offset so the details of each may be seen. The two mine target examples are a VS-50 (grid location B04) and an M-14 (grid location B16); both buried at a depth of approximately 1 inch. The two clutter examples are a flat stone (grid location E07) and a tree root (grid location E25). These examples illustrate the fact that the GPR signal differs across targets. The depth of a target appears in the GPR signal as a time delay relative to the ground bounce, with deeper targets exhibiting a longer delay. The strong return present in each of the signals at a time of about 2ms is the ground bounce. Notice the ground bounce for the mine targets is much stronger than the ground bounce for the clutter targets. This anomaly is due to the fact that during data collection external variables, such as the array gain, were not held constant for all targets. Therefore, artifacts associated with the data acquisition, such as differences in the ground bounce amplitude or total signal energy, were removed before the data was analyzed.

3. SIGNAL PROCESSING FOR ATR USING THE BRTRC WICHMANN GPR SYSTEM

Signal detection theory states that the likelihood ratio is the basis for making the optimum decision between two hypotheses. This approach provides the foundation for the signal processing algorithms applied to the BRTRC Wichmann antenna array GPR data. In this context, the hypotheses are

$$H_0: \quad \text{clutter}$$
$$H_1: \quad \text{mine}$$

The likelihood ratio, $\Lambda(\mathbf{r})$, is defined as the ratio of the probability of the observation occurring under H_1 to the probability of the observation occurring under H_0;

$$\Lambda(\mathbf{r}) = \frac{p(\mathbf{r}|H_1)}{p(\mathbf{r}|H_0)} \tag{1}$$

where $\mathbf{r}$ represents the measured data and $p(\mathbf{r}|H_i)$ is the probability of the observation occurring under hypothesis i. In order to implement this approach, it is necessary to first determine the signal and noise models so the probability density functions can be defined. It is also necessary to accurately model any uncertainties in the parameters defining the signal, such as the target depth.

If the data follows an uncorrelated multivariate Gaussian distribution with zero mean and variance σ^2 under the null hypothesis $\left(\mathbf{r} \sim N(\mathbf{0}, \sigma^2\mathbf{I})\right)$ and known mean $\mathbf{s}$, and the same variance under the alternate hypothesis $\left(\mathbf{r} \sim N(\mathbf{s}, \sigma^2\mathbf{I})\right)$, then the likelihood ratio reduces to a matched-filter which can be implemented as $\mathbf{s}^{\mathrm{T}}\mathbf{r}$. It is important to note that the matched-filter is optimal only if the assumptions regarding the distributions of the data under both hypotheses are accurate. Although the matched-filter is not the optimal approach in many situations, it is a starting point from which to evaluate preliminary algorithms and to build more complex algorithms.

When the signal observed under H_1 is variable, the uncertainty in the parameters defining the signal may be incorporated directly into the likelihood ratio through conditional probability density functions;

$$\Lambda(\mathbf{r}) = \frac{\int_{\theta} p(\mathbf{r}|\theta, H_1)\, p(\theta)\, d\theta}{p(\mathbf{r}|H_0)}, \tag{2}$$

where θ represents the set of uncertain parameters. In general, a likelihood ratio that incorporates the uncertainty associated with the signals is more complicated to implement than a matched-filter, which does not incorporate any signal uncertainty. An example of this scenario is the situation where more than one type of mine may be present, and each of the M possible mines possesses a unique signal. The hypotheses for this situation are

H_0: clutter

H_1: any 1 of M mines

The corresponding likelihood ratio is

$$\Lambda(r) = \frac{\sum_{m=1}^{M} p(r \mid \text{mine}_m, H_1)\, p(\text{mine}_m)}{p(r \mid H_0)}. \tag{3}$$

The likelihood ratio formalism may be also extended to include clutter models. One approach is to model the clutter statistically, and then modify $p(r \mid H_0)$ to reflect the clutter statistics. This approach is appropriate when there are many example clutter signatures available on which to build the clutter model statistics, and the set of possible clutter targets is very large. Uncertainties in the parameters defining the clutter signals may also be incorporated into the likelihood ratio;

$$\Lambda(r) = \frac{\int_{q_1} p(r \mid q_1, H_1)\, p(q_1)\, dq_1}{\int_{q_0} p(r \mid q_0, H_0)\, p(q_0)\, dq_0}. \tag{4}$$

When the number of available clutter signatures is limited and the set of possible clutter targets is small, it is possible to use the example clutter signatures, rather than a stochastic model intended to represent all clutter, to compute $p(r \mid H_0)$. For the situation where there are N possible clutter targets, the likelihood ratio is

$$\Lambda(r) = \frac{\sum_{m=1}^{M} p(r \mid \text{mine}_m, H_1)\, p(\text{mine}_m)}{\sum_{n=1}^{N} p(r \mid \text{clutter}_n, H_0)\, p(\text{clutter}_n)}. \tag{5}$$

Due to the limited amount of data available, this is the likelihood ratio implemented for the mine detection performance analyses when a clutter model is incorporated.

4. ANALYSES PERFORMED

This preliminary investigation focused on analyzing the one scan taken directly over the target. The remaining 4 scans were not utilized for mine detection in this work, but will be considered in future work. Since external variables, such as the array gain, were not held constant across all targets during data acquisition, cues associated with the energy level must be removed before the data is processed. Generally, mine signatures were collected with high antenna gain and clutter signatures were collected with low antenna gain. Three approaches to remove the energy level cues were considered. The first method normalizes the total signal energy in each trace to unity. This approach removes all the differences in the energy levels of the recorded mine and clutter data which would otherwise unfairly improve detection performance. However, it also removes any inherent, and fair, differences in the energy of mine and clutter signals. This normalization method also renders an energy detector useless since all energy information is removed in the normalization process. The second approach is to normalize the maximum amplitude of the ground bounce for a single trace (trace 4 was chosen) to unity, and then apply the same normalization factor to the remaining traces. This approach retains the inherent differences in the energy levels of mine and clutter signals, and removes the differences attributable to the variation in the array gain. However, it also assumes the ground bounce amplitude is not affected by the presence of a surface flush target. This is not necessarily true, and this approach to normalization removes any information associated with the ground bounce amplitude. The third normalization method utilizes the two outermost traces (1 and 8) from both of the two outermost scans (1 and 5) to calculate the average ground bounce for a particular target. The maximum amplitude of the average ground bounce is normalized to unity, and the required normalization factor is applied to each of the traces in the center scan. This approach retains the information in both the maximum ground bounce amplitude and the relative energy level of the recorded signal. However, it also assumes the array gain is constant for each target. This last approach is the normalization method utilized for the results presented in this paper.

A second issue that must be addressed is the signal timing. The height of the sensor above the ground was not constant across scans or targets. Slight variations in the sensor height appear as variations in the time at which the ground bounce occurs in the recorded signal. This is evident in the example signals shown in Figure 1. The ground bounce occurs in each of the signatures at a time of approximately 2ms, but there are variations in the exact time at which the ground bounce occurs. If these differences in the signal timing are not considered, performance with the matched-filter approaches is adversely affected. The signal timing is normalized by time-aligning the ground bounce for the center trace, and then applying the same alignment factor to the remaining traces.

The quantity of data collected with the BRTRC Wichmann GPR system is quite small due to the limited amount of time (2 days) available for data acquisition. Therefore, training data, in the form of multiple passes across each target, were not collected. This leads to the issue of incestuous data when evaluating algorithm performance. Several approaches were considered to address this problem. The first approach is to use half of the traces for training (2, 4, 6, 8) and the remaining half for testing (7, 5, 3, 1). The problem with this approach is that only half the data is utilized, so ultimate performance bounds with the BRTRC Wichmann antenna array are not estimated. The second approach is to train on all 8 traces (1-8), and then test on all 8 traces in reverse order (8-1). Both of these approaches exploit the symmetry in the geometry of the mine targets to “create” a second data set. The third approach is to use the measured signal as the “known” signal and then add noise to create simulated data for performance evaluation.

5. MINE DETECTION PERFORMANCE

Two types of detection algorithms are implemented. The first does not include a clutter model, and the clutter signals are modeled simply as uncorrelated zero mean Gaussian random variables [Eq. (3)]. The second type of algorithm includes a clutter model. In this case, the clutter is modeled as one of N possible clutter targets [Eq. (5)]. In addition to investigating two types of detection algorithms, several detection scenarios of increasing complexity are considered. The first hypothesized situation is one in which the both the mine type and its burial depth are known *a priori*. Detection performance in this case is evaluated for the discrimination of a single mine type at a known depth versus all possible clutter targets. The second scenario is one in which the mine type is known *a priori*, but its burial depth is uncertain. For this case, detection performance is evaluated for a single mine type at all measured depths versus all possible clutter targets. The final hypothesized scenario is one in which neither the mine type nor its burial depth is known *a priori*. Detection performance for this case is evaluated for all measured mine signals versus all possible clutter targets. Results are presented for each of the detection scenarios using both detection algorithms (with and without clutter model) and normalizing the recorded signals with respect to the average ground bounce. There are 12 mine targets and 10 clutter targets utilized in the following analyses.

1. Detection of a Known Mine Type at a Known Depth

The simplest detection scenario is when there is no uncertainty regarding either the mine type or its burial depth. Three detection algorithms implemented, an energy detector, a likelihood ratio without a clutter model, and a likelihood ratio with a clutter model. All 8 cross-track traces are utilized, and the data is reverse ordered for training and testing the algorithms. The probability of false alarm corresponding to perfect detection performance (100%) of each of the mine targets considered in this work is listed in Table 1. The false alarm probability was determined by setting the threshold equal to the output of the detector when the mine was present, and then determining the fraction of the clutter targets with detector outputs greater than or equal to the threshold. These results should be viewed cautiously due to the limited amount of data available. However, for the majority of the mine targets, there is a substantial reduction in the false alarm probability when a likelihood ratio detector is implemented, particularly when a clutter model is included. The deterioration in performance observed for the VS-50 at 1”depth can be attributed to anomalies in the data. In performing this analysis, it was assumed that the data recorded for each target was symmetric so that the incestuous data issues could be avoided by reverse ordering the traces for training and testing. The assumption does not hold for data collected for the VS-50 at 1” depth.

Mine Type, Depth	Energy Detector	LR without clutter model	LR with clutter model
VS-50, 0”	50%	0%	0%
VS-50, 1”	50%	90%	80%
VS-50, 1.875”	10%	0%	0%
M-14, 0”	80%	0%	0%
M-14, 1.06”	20%	20%	0%
M-14, 1.875”	10%	0%	0%
PMA-3, 0”	20%	10%	0%
PMA-3, 1.75”	80%	0%	0%
VAL69, 0”	70%	0%	0%
VS-2.2, 3.25”	60%	0%	0%
M-19, 1.75”	20%	0%	0%
M-19, 2.5”	0%	50%	0%

Table 1: Probability of false alarm corresponding to perfect detection of a known mine type at a known depth using 8 traces (non-incestuous data).

2. Detection of a Known Mine Type at an Unknown Depth

A slightly more complicated detection scenario is one in which the mine type is known *a priori*, but its burial depth is not. This data set contained two mines for which there were measurements made at three burial depths; the VS-50 and the M-14. The detection performance for both of these mines is presented here. The results are presented as a function of the number of traces utilized by the detection algorithm for both incestuous and non-incestuous data. Bu evaluating the performance with incestuous data, a performance bound can be determined. The detection algorithms are an energy detector, a likelihood ratio without a clutter model, and a likelihood ratio with a clutter model. For the performance with incestuous data, the matched-filters used by the likelihood ratios are defined by the same data on which the algorithms are tested. For the performance with the non-incestuous data using all 8 traces, the matched-filters used by the likelihood ratios are defined by the data in forward order (1-8) and the algorithms are tested on the data in reverse order (8-1). The single trace results are for a center trace (4), and the results with half that data are for traces (2, 4, 6, 8). The non-incestuous results for these cases are determined by testing with trace 5, for a dingle trace, and with traces (7, 5, 3, 1) for half the data. The performance attained with incestuous data provides an upper bound on the performance that can be expected with this particular data set. A likelihood ratio with a clutter model achieves perfect detection performance in all instances when operating on incestuous data. A likelihood ratio detector with a clutter model generally outperforms an energy detector with the non-incestuous data as well.

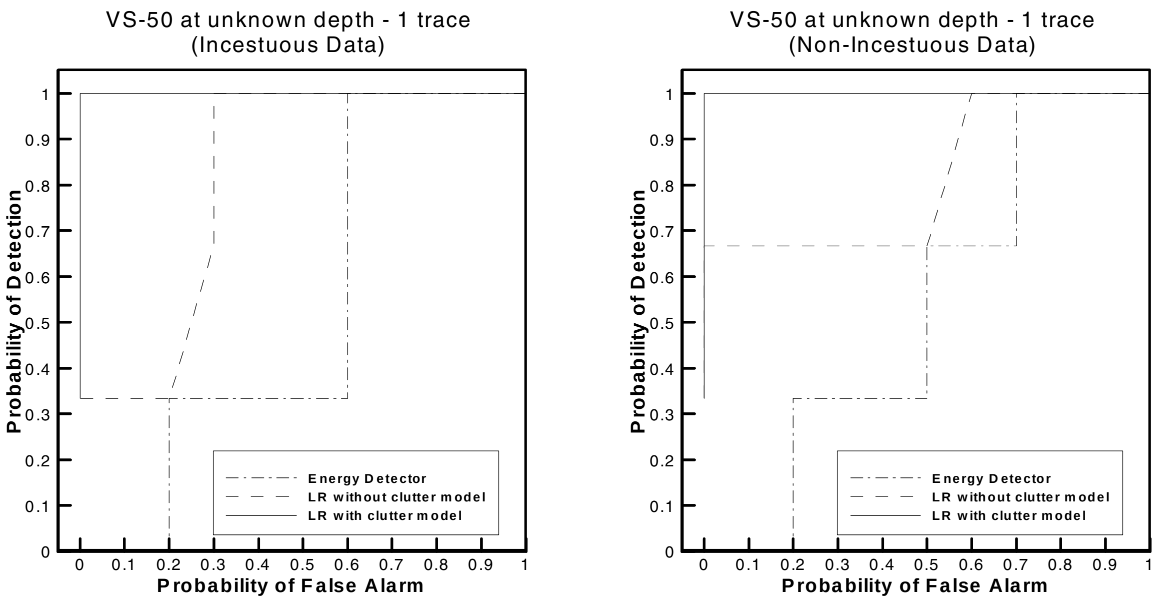

Figure 2: Detection of a VS-50 at an unknown depth using 1 trace.

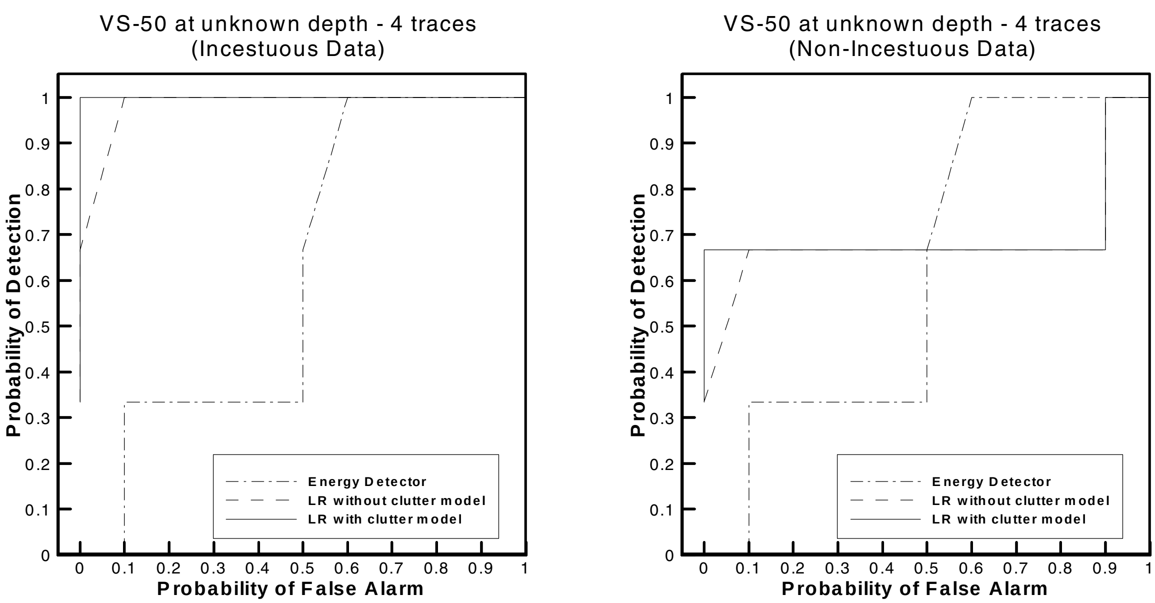

Figure 3: Detection of a VS-50 at an unknown depth using 4 traces.

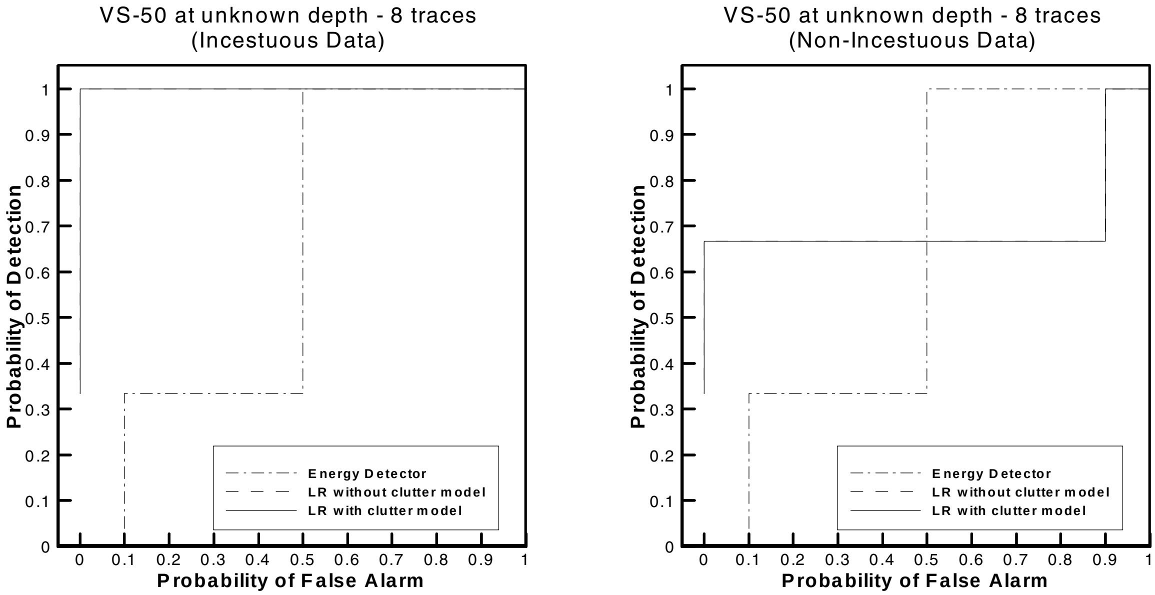

Figure 4: Detection of a VS-50 at an unknown depth using 8 traces.

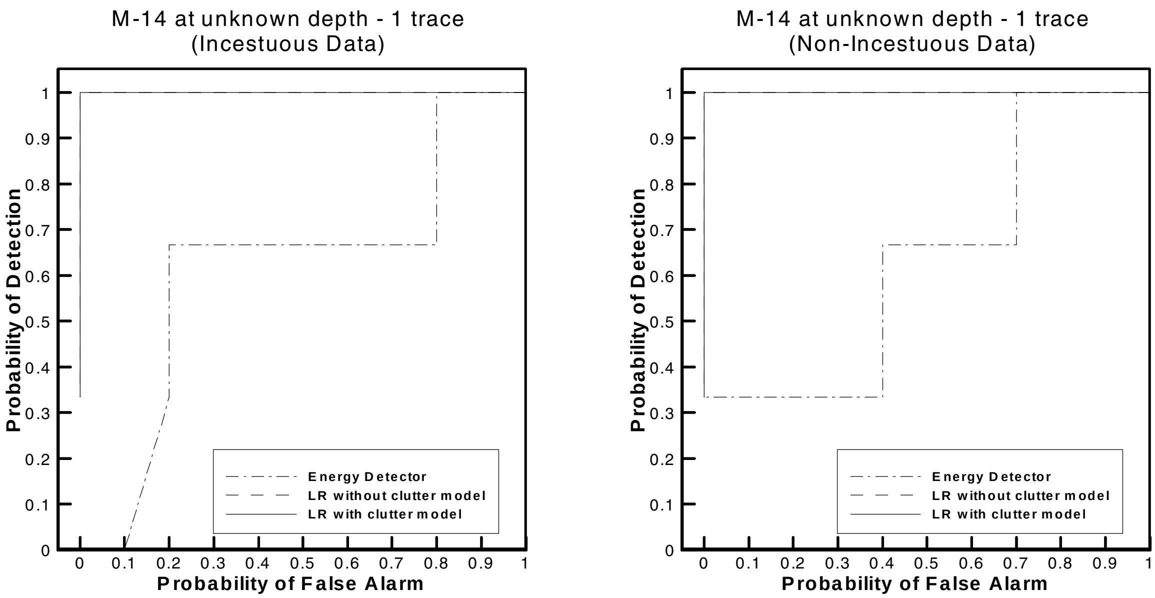

Figure 5: Detection of an M-14 at an unknown depth using 1 trace.

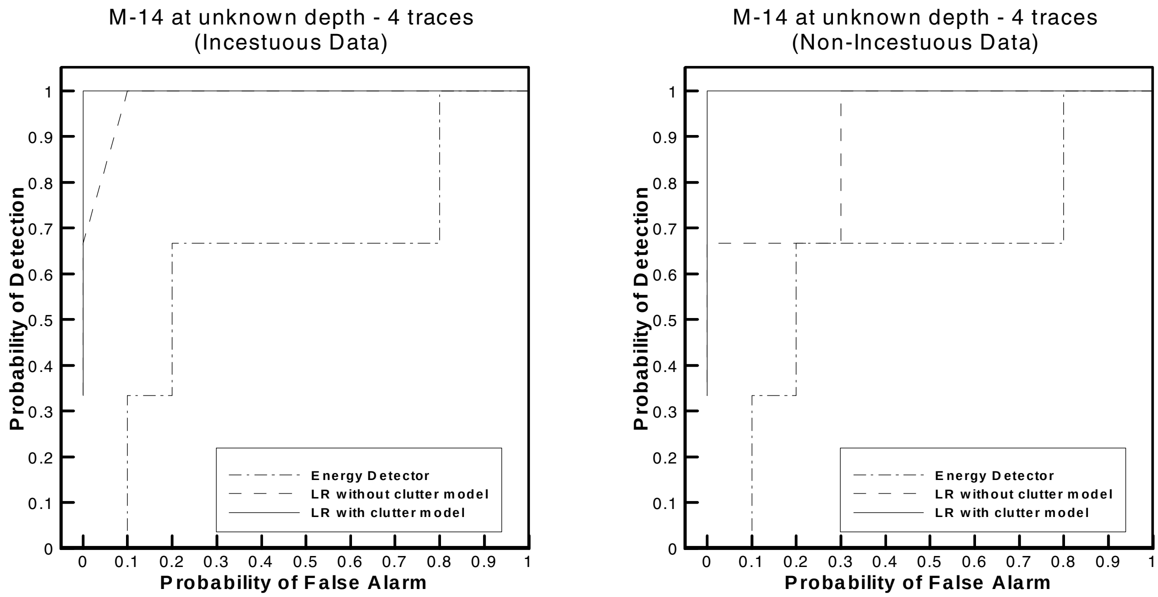

Figure 6: Detection of an M-14 at an unknown depth using 4 traces.

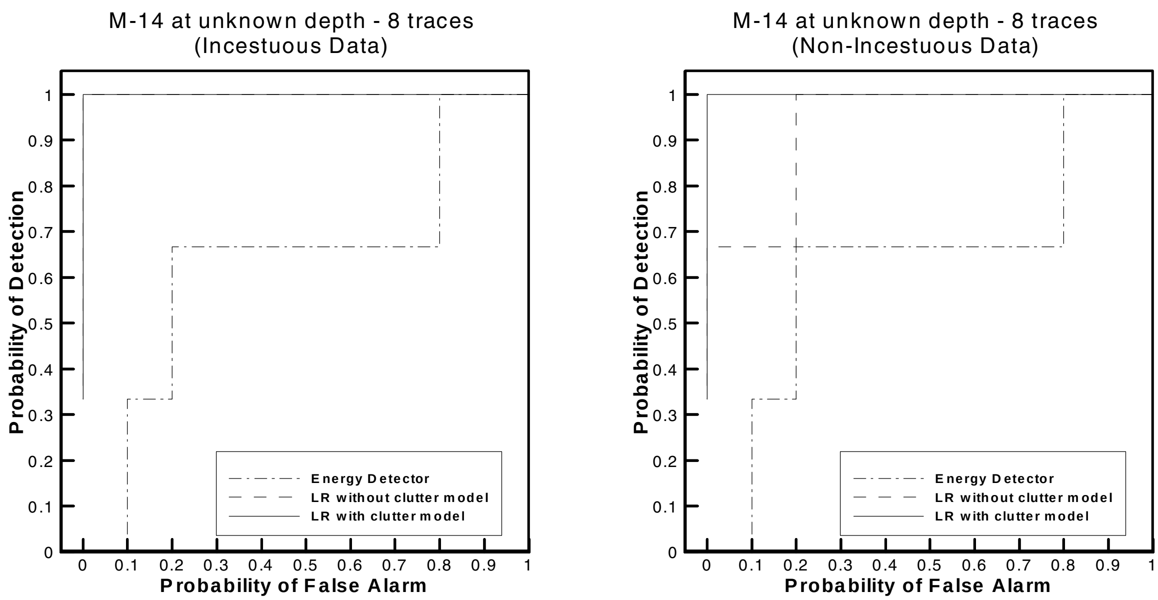

Figure 7: Detection of an M-14 at an unknown depth using 8 traces.

3. Detection of an Unknown Mine Type at an Unknown Depth

The final scenario considered is the detection of an unknown mine type at an unknown depth. This is the most complex of the three situations analyzed with this data. The results are presented as a function of the number of traces used by the detection algorithm. The likelihood ratio detector outperforms the energy detector in all cases, and this level of performance is maintained even when substantial levels of noise are added to the recorded signals. Further, detection performance is improved when a clutter model is incorporated into the detection algorithm. These results illustrate that incorporating representative realizations of the target and clutter signatures improves the detection of buried mines, and that mines can be differentiated from clutter using a ground penetrating radar system.

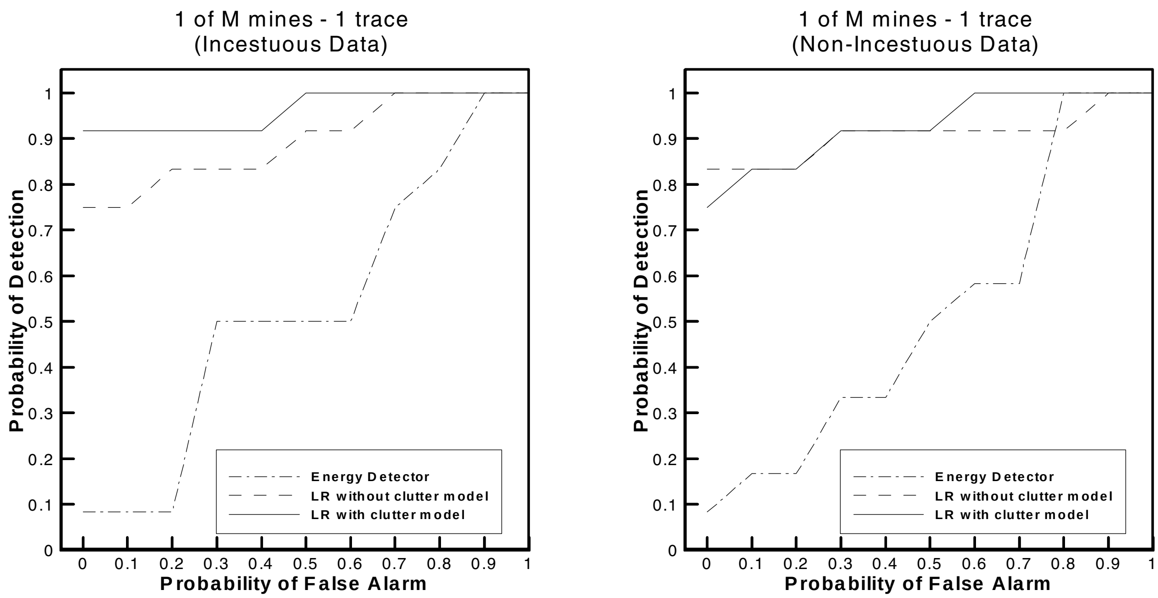

Figure 8: Detection of an unknown mine at an unknown depth using 1 trace.

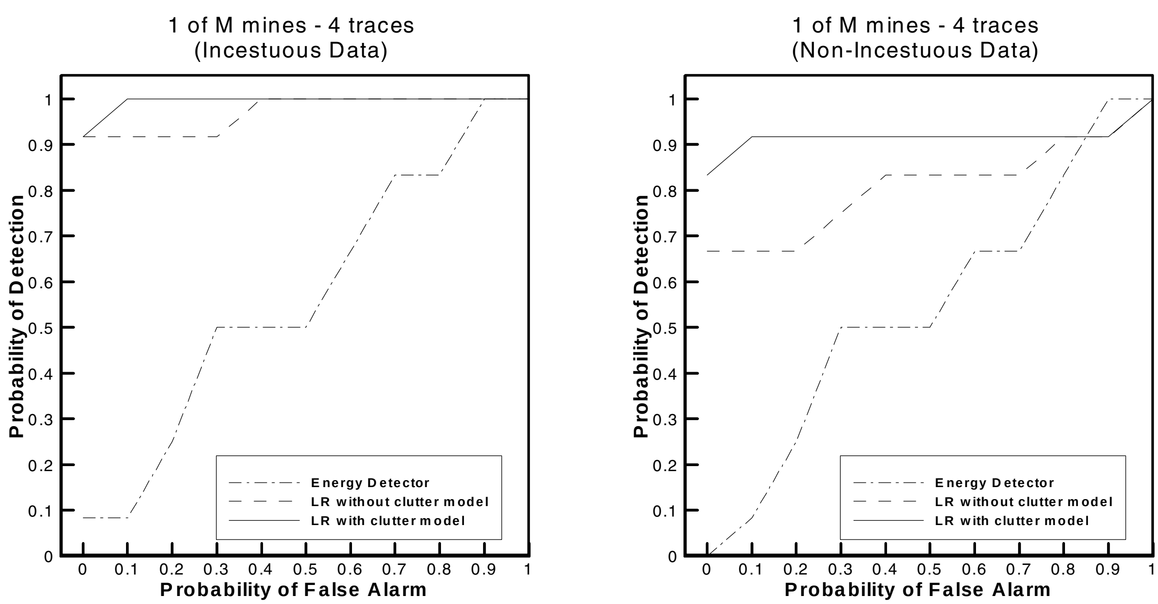

Figure 9: Detection of an unknown mine at an unknown depth using 4 traces.

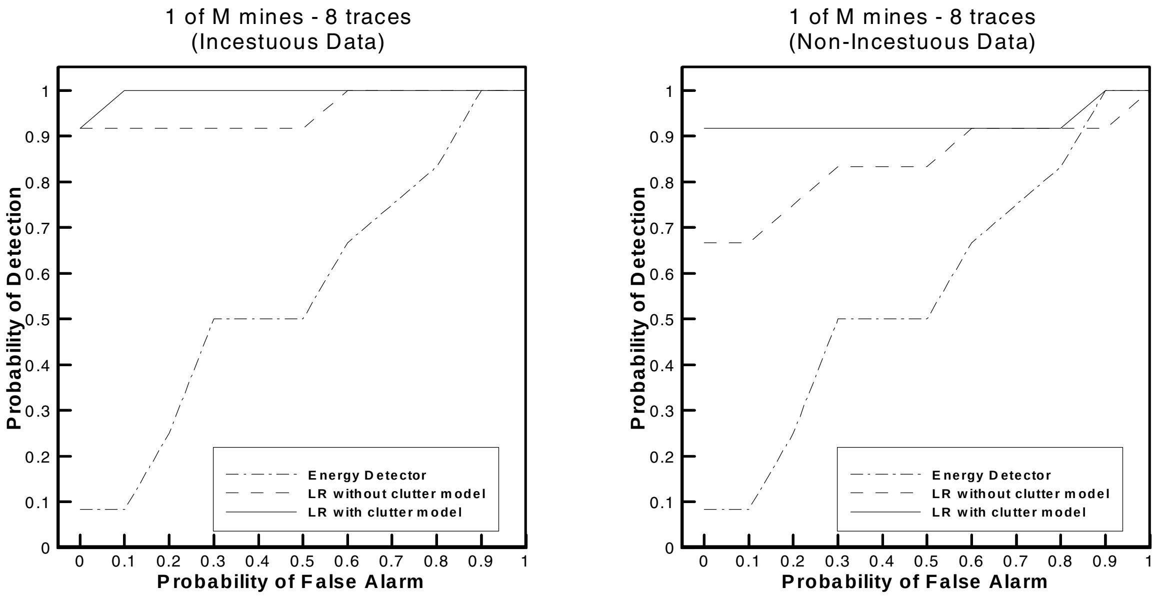

Figure 10: Detection of an unknown mine at an unknown depth using 8 traces.

6. SUMMARY

Preliminary results with a limited data set collected with the BRTRC Wichmann antenna array indicate that mines can be successfully differentiated from clutter using GPR. The utility of statistical approaches for target detection is also illustrated via comparison to a standard energy detector. These results should be viewed cautiously due to the limited amount of data available for analysis. However, the preliminary results demonstrate very good detection performance when a likelihood ratio is implemented, particularly when a clutter model is included.

The likelihood ratio approach implemented here is essentially a matched-filter approach, and it does not rigorously incorporate any of the uncertainties likely to be found in a "real-life" application. These uncertainties include variable sensor height, variable object depth, objects that are not necessarily centered in the field of view, and multiple objects in the field of view. Additional future work involves using the spatial information contained in the down-track scans to improve detection performance. A better clutter model and model-based target signatures, rather than estimating the signatures from measured data will also improve the likelihood ratio detection performance. Finally, these results should be validated with more data so that the issues of incestuous data associated with such a small data set can be avoided.

7. ACKNOWLEDGEMENTS

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